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Research Article

ROBUST SPONTANEOUS HUMAN BEHAVIOUR PREDICTION SYSTEM IN HEALTHCARE

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ABSTRACT

Machine understanding of the human mind through facial expression is a challenging research area of human machine natural intelligent interaction. This paper proposes a novel framework for human mind recognition in real time mode. We used Viola-Jones face detection technique to detect the faces in the image. These active image sequences are filtered with low pass Gaussian mask to remove the noises. Salient emotional features are segmented from the face using our novelty idea, our proposed work achieved 94.14% recognition rate using Local binary pattern feature extraction with Support vector machine classifier. Our methodology tested on both CK+ and JAFFE database, and our developed work found to perform well in e-health and e-learning systems consistently in different resolution and yet require significantly less execution time.

Keywords: Viola-Jones, Gaussian mask, emotional features, Support vector machine, Local binary pattern.

INTRODUCTION

Analyzing of human emotional intelligence through the digital image processing algorithm is a modern research work in the field of computer vision[1]. Automatic recognition of emotion from facial expression has been an interesting and challenging research topic in the area of affective computing systems for more than 40 years. The human face is a dynamic object and has a high degree of variability in its appearance, which makes face detection itself difficult problem in the emotion recognition work. In our modern life, machine replaced the human role in all the fields. It functions like as humans to perform our routine job. The most important reasons to consider machine is its user friendliness and low cost. Human invented computer which processes the numerical data in a picosecond speed with more accuracy than a human being but human beings score over computer in recognition capability and judgments. Computers are good in numerical processing but poor in understanding an image. To full fill these gaps between human-machine interactions, researchers are concentrating more and more on computer vision problems.

Facial expression conveys the state of person's mind. Facial emotion recognition systems (FERS) means finding the inner mind of the humans, i.e. such as anger, disgust, fear, happiness, sadness and surprises by the clue of recognizing facial expression. To truly achieve an effective human-computer interaction's computers want to understand the facial expression like human to human communication. The face is the most powerful nonverbal channel for human communication. Many modalities[2] (fig. 1) are used to recognize the emotion of human, among these visual perceptions of facial expression contains much information about the person id i.e. a face is the index of the mind (Napoleon Bonaparte says that a picture worth thousands of words). Emotions positively affect the intelligent functions such as decision making, perception and empathic understanding.

Applications: The research work of an automated FERS attracted a lot of attention due to its wide applications[3,4] in the area of authentication (entrance security, information security, driver license, mug shot match), discrimination of real from the faked expression of pain, healthcare monitoring, automatic access control systems, autism spectrum disorder support, detection of driver fatigue, online tutoring systems, behavior understanding, online customer satisfaction studies, entertainment (intelligent music player, TV and games), intelligent robotics, smart rooms, crowd surveillance, video conferencing and so on.

Human can easily recognize emotion of the human through facial expression, but it is quite hard for a machine as smart as human. Even though the technology of emotion recognition is demanded in various fields, it still remains as unsolved problems[5] in several circumstances. Particularly on illumination variations, face occlusion, low resolution images, head and pose variations, color of the images, landmarks distance variations, absence of a neutral face for comparison. The main objective of our work is to develop a system that should have the capability to understand the patient's mood in clinic by recognizing his/her facial muscle contractions.

MATERIALS AND METHODS

Related works

An expression analysis system started in the nineteenth century, in 1872. Charles Darwin father of evolutionary biology was the first person who proposed and demonstrated some of the facial expression. E.T. Hall[6] mentioned in his work, between 60-80 percent of the message is communicated through our body language and only 7-10 percent is attributes to the actual words of a conversation. According to Mehrabian[7] studies human infer information from verbal 7% (speech), vocal 38% (tones of words) and facial expression 55%, this shows that facial expression have a unique role among other modality.

In1960's American psychologist Silvan Solomon Tomkins[8] conducted the first study demonstrating that facial expressions are in fact reliably associated with some certain emotional states. In 1971 American psychologist Ekman[9] defined six basic emotions of humanity which are universal in human culturing. A system developed by a Swedish anatomist Carl-Herman Hjortsjo[10] was later adopted by Ekman in 1978, developed the facial action coding system (FACS).

In 1991, Kenji Mase[11] used Optical Flow methodology to recognize facial expressions. He was the first person who used image processing techniques to recognize facial expressions. In his work he used eight directions of optical flow changes to detect the movement of FACS. Sirovich and Kirby developed approach of eigenfaces to recognize later it was used by Matthew Turk and Alex Pentland[12] for facial classification. Rosenblum et.al.[13] computed optical flow of regions on the face, and applied a radial basis function network to classify expressions. Ekman et.al, revised the FACS used to describe the 2D facial images of a person.

In 2005, Wen qin and Wang Zeng-fu[14] proposed the 3-Dimensional data based method for recognizing FER. P. S. Aleksic and A. K. Katsaggelos[15] developed the automatic facial expression recognition systems using MPEG-4 standard support to facial animation parameters and multi streams HMMs, achieved the 93.66% recognition rate. Anderson and McOwan[16] achieved 81.82% recognition rate in their work.

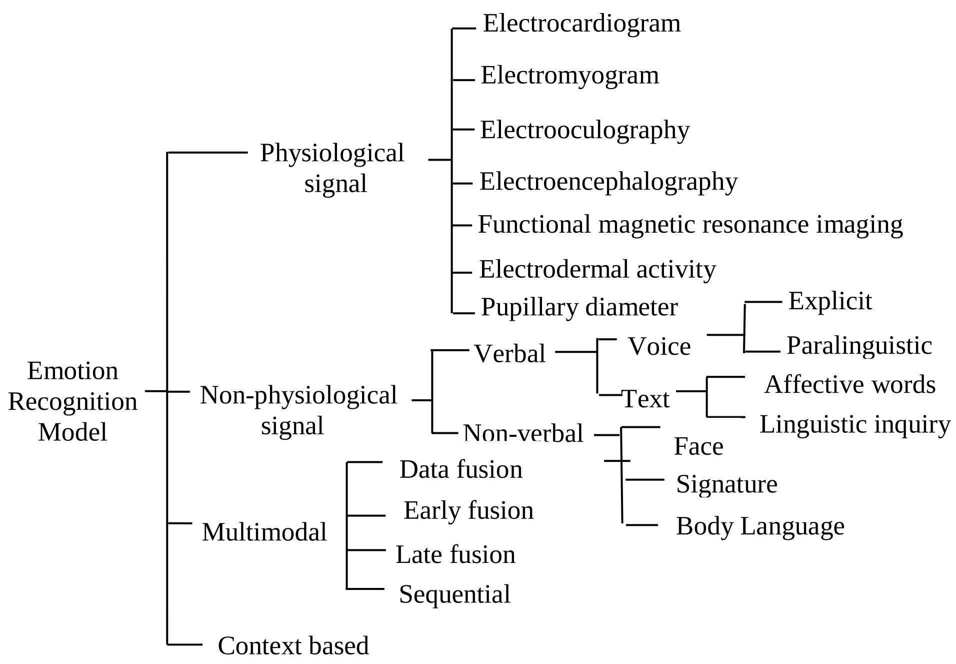


Figure 1: Emotion recognition taxonomy

Irene and Ioannis[17] experiment result shows 99.7% accuracy, using the multiclass support vector machine on the Cohn-Kanade (CK) database and 95.1% accuracy on facial action unit. Stefanos Zafeiriou and Ioannis Pitas[18] proposed the elastic graph matching technique to recognize facial expression and Achieved 90.5% recognition rate in Gabor based elastic graph matching method and 91.8% recognition rate in normalized morphological based elastic graph matching method. Tong and others[19] have achieved the recognition accuracy of 88.3% by using the Deep Belief Networks classifier algorithm. Zhang in his patch-based Gabor method obtained the recognition rate 92.92% on JAFFE database.

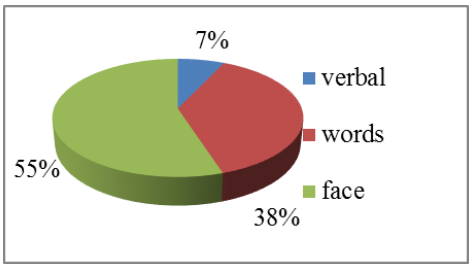


Figure 2: Mehrabian's study

Seyed Mehdi Lajevardi and Hong Ren Wu[20] introduced the tensor perceptual color framework to recognize facial expression and achieved 68.28% accuracy in CIELuv color space. Valstar and Pantic2[21] in the year of 2012 achieved 95.3% with combination of gentle boost, support vector machine and hidden Markov models. Li and et.al achieved 94.05% recognition accuracy on fusion of Dynamic Bayesian network and Adaboost classifier. Wu and et.al[22] achieved the 88.33% recognition accuracy, using template matching methods.

PROPOSED MODEL

Our novelty work has following stages: face detection, preprocessing, expression landmark detection, feature extraction and classification.

Face localization

Localizing faces in the input scene is the stepping stone to all facial analysis algorithms, so face detection has placed the first step in every automatic FERS. The primary goal of face detection in FERS is to highlight the face region of the input image into segments the face area from the image background.

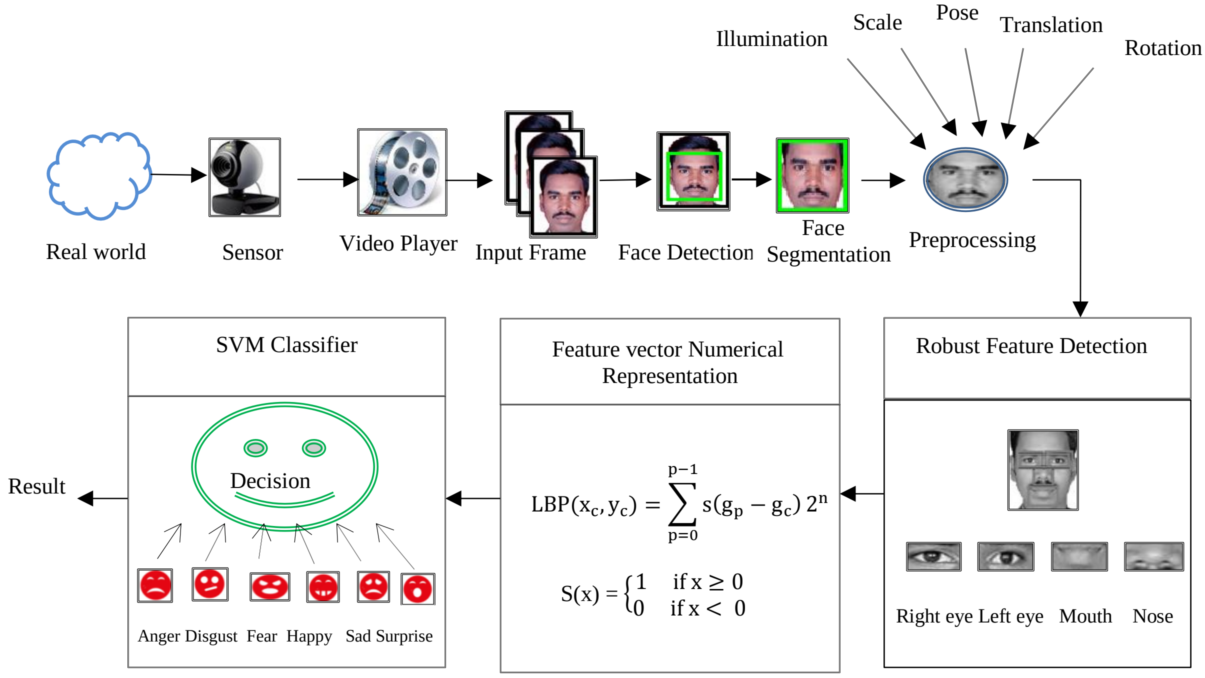


Figure 3: Proposed methodology workflow

When computers are able to understand the faces fully, then they can understand the thoughts and intentions oh humans for a real time communication. Face detection[23] uses mathematical techniques on the pixel values or features in the facial area of an image to determine the location of any faces within an image. Face detection appears as a trivial task for human beings, but an extremely tough task for computers. Reliability of face detection has the major influence on the performance and usability of the entire FERS. Two forms of input model for the face detection is static and dynamic model. In dynamic form of input detected faces are tracked across multiple frames using a face tracking component.

Implementation of face detection itself a great challenge, so accuracy of the detection rate heavily depends on the scenario of controlled environment, color of images, image motion, pose variation (out-of-plane rotation), orientation (in-plane-rotation), feature occlusion, an expression of the face, image conditions, beard, mustache, glasses, and so on. In this work face area in an image is detected by using the well-known Viola-Jones[24] face detection method that is based on the Haar-like features and the Adaboost learning algorithm. This method builds a fast and robust to non-frontal faces, multi-view faces and also provides competitive object detection rates in real time.

Preprocessing

Image preprocessing is a prior process of input data, before moving to feature extraction this step makes the image easier to process the data and increase the chances of getting correct classification matches. The main aim of the preprocessing an image is to obtain sequences of images which have normalized intensity, uniformed size, shape and reduce the feature dimensions by increasing the processing speed it depict only the face region. The cropped face is passed through 3 x 3 Gaussian mask low pass filter[25] to remove noises in the image. Histogram lighting normalization technique is used for illumination corrections.

Expression landmark detection

Human behavior prediction is the process of pipelining work where the output of one level is the input to the next level, so accurate facial landmark detection is the key work in human behavior prediction systems, the prominent landmarks are eyes, mouth, nose, eyebrows and lips. In our proposed work both left and right eyes are cropped using Haar classifier with Adaboost learning[26] techniques, similarly we have cropped the position of nose. Mouth is localized using the position of the nose as hints. Lip corners were localized using the horizontal central line of the cropped mouth. Eyebrows were localized using the source of eye positions.

Algorithm

Eyebrows corner detection
Input: gray scale image-face
1. Identify the location of eyebrows separately using the position of both left and right eyes

2. To apply low pass filter 3x3 Gaussian mask to the eyebrows ROI
3. To apply Canny edge detection operator
4. Convert gray into binary image
5. To apply Otsu-thresholding
6. To apply morphological thicken operation
7. Remove the unwanted-small component using threshold technique
8. Locate the left and right most positions of connected component as lip corners

In some situations, due to shadow below the hair styles, eyebrows were not detected properly. By using the above mentioned steps error rate were minimized for detection of eyebrows and lips features.

Feature extraction

Feature extraction and representations are critical in automatic facial expression recognition systems. Emotional feature extraction is performed on the cropped landmark image. To extract salient information that is useful for distinguishing facial expression of different persons. This technique is robust with respect to the geometric and photometric variations. Facial feature extraction methods are majorly classified as appearance, geometric, and hybrid method. Local binary pattern[27] method was widely used as a robust illumination invariant feature descriptor. This operator generates a binary number by comparing the neighborhood pixel values with the center pixel value. In a given image, pixel at (x_c, y_c), the LBP result can be expressed in decimal form as,

$$LBP(x_c, y_c) = \sum_{p=0}^{p-1} s(g_p - g_c)\, 2^n$$

n-runs over the 8 neighbor of the central pixel g_p and g_c are gray level values of the central pixel and the surrounding pixels, the function S(x) is defined as,

$$S(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

In a 3 x 3 pixel block of an image pixels are threshold by its center pixel value. The neighborhood consists of 8 pixels; a total of 2^8=256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood. A drawback in the LBP operator is noise sensitivity and lack of rotational invariance.

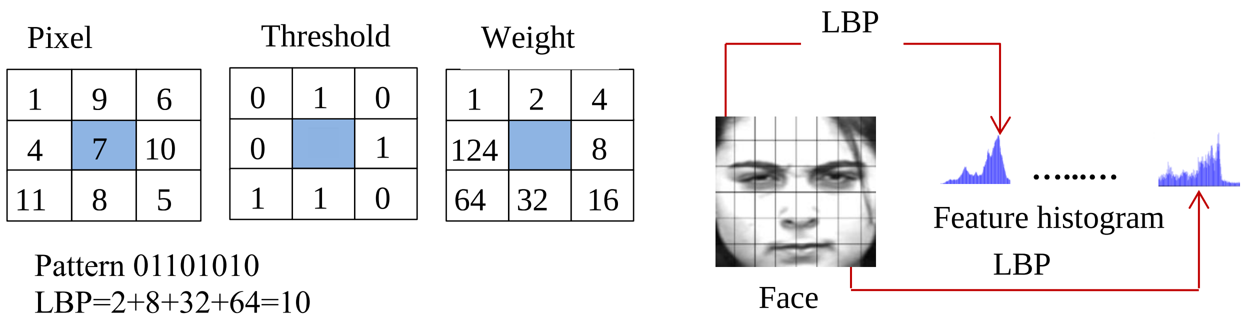
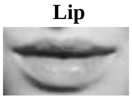


Figure 4: The LBP operator and its histogram

TABLE 1: Feature shape deformation for different expression

Emotion	Features							
	Cheek 	Eye 	Eyebrows 	Eyelid 	Jaw 	Lip 	Mouth 	Nose 
Anger	-	Open	Outer: down, Inner: up	Both pulled up	-	Stretched thin & tight	Closed	Flaring nostrils
Disgust	-	-	Pulled down	-	-	Upper: curled & raised Lower: depressor, Extreme case: teeth visible	-	Wrinkled
Fear	-	Wide-Open	Inner: raised, Outer: down	Lower: tense Upper: raise	Dropped	-	Open, corner stretched and pulled back	-
Happiness	Raised	Open-wrinkle around	Relaxed	-	-	Corner pulled up	Open, edge up	-
Sadness	-	Closed	Outer: down, Inner: raise (go up together)	-	-	Corner pulled down	Edge down	-
Surprise	-	Wide-open	Raised	Upper-wide open Lower-relaxed	Dropped (open)	-	Open drop	-
Neutral	-	-	-	Eyelid tangent to the iris	-	Lips in context	Closed	-

Classifier

Information extracted from the face is the input for expression classifier. There are many machine learning classifiers available to classify the expressed image into one of the emotional class. The robust classifier for emotional label classification is support vector machine, so in our work we used to SVM classifier to classify[28] the extracted features into one of the basic emotion of anger, disgust, fear, happiness, sad and surprise. SVM maps the feature vector in to different plane, there are many kernels (linear, polynomial, and radial basis function) have been used on SVM classifier among that RBF kernels performing superior classification.

RESULT AND DISCUSSION

Data set

Our methodology were trained and tested on both CK+ and JAFFE database. CK+ database contains 593 total images with male and female having seven facial expressions, posed by 123 subjects, color of the image is gray with uniform size of 640 x 490, for experiments on CK+ database, we used 310 images in total: anger (39), disgust (42), fear (49), happiness (65), sadness (53), and surprise (62). JAFFE database contains 213 total image sequences of female posed by 10 models, color of the image is gray with uniform size of 256 x 256 for experiments on JAFFE database, we used 180 images in total: anger (30), disgust (31), fear (29), happiness (30), sadness (30), and surprise (30). Table 2 shows the performance of the proposed work with different approaches on expression recognition system.

Performance measure

The system performed good for surprise expression and worst for anger expression, the classification error rate was maximum (5.85) between anger and sadness, all the experiments done standard of 96x96 face resolution. Our proposed work achieved 94.14 percent accuracy on overall average recognition rate on CK+ Database, The system performed good for surprise expression and worst for anger expression, the classification error rate was maximum (5.85) between anger and sadness. 96 x 96 face resolution. An overall 91.92 percent accuracy was achieved on JAFFE database. In table 4 the testing of the given input image for six universal expressions have been performed. The expression that gets the more number of votes is considered as the dominant expression. From table 4 expression sad won the maximum number of votes. Thus decided expression of the testing image is sad.

TABLE 2: Performance comparison of the different approaches

Authors	Features	Classifier	Database	Classification rate of each label						Recognition rate
				Anger	Disgust	Fear	Happy	Sad	Surprise	
Yongqiang et. al.[29]	Gabor filter	AdaBoost + DBN	CK+	66.67	91.02	80.00	97.08	80.00	96.88	87.43
S.L.Happy et.al[30]	LBP	SVM	CK+	87.8	93.33	94.33	94.2	96.42	98.46	94.09
Ligang Zhang et. al[31]	Gabor filter	SVM	JAFFE	96.67	90	93.75	93.55	93.55	90.00	92.92
Yogp chandran et. al[32]	LFDA	Nearest neighbour	JAFFE	96.7	93.1	93.8	93.5	90.3	93.3	94.37
Our work	LBP	SVM	CK+	89.2	93.26	93.91	94.81	96	97.66	94.14

TABLE 3: Proposed work confusion matrix of CK+ Database

	Anger	Disgust	Fear	Happy	Sadness	surprise
Anger	**89.2**	0	0	0	5.85	4.95
Disgust	0	**93.26**	1.76	0	2.42	2.56
Fear	0	0	**93.91**	3.90	0	2.19
Happiness	1.42	2.46	0	**94.82**	0	1.30
Sadness	2.32	0	0	1.68	**96**	0
Surprise	0	0	0	2.34	0	**97.66**

TABLE 4: Testing dataset

Test image	Features	Number of votes for the selected features						Result
		Anger	Disgust	Fear	Happy	Sad	Surprise	
	Left eye	1	0	2	0	2	0	Sad
	Right eye	0	2	1	0	2	0	
	Nose	2	1	0	0	2	0	
	Lip	0	0	1	0	3	1	
	Total votes	3	3	4	0	9	1	

CONCLUSION

In the modern world digital revolution is taking place everywhere, so world is changing too fast never seen before like this. The goal of every smart work is lowest, cheapest and quickest action. Likewise all universities are offering e-learning courses. In e-learning, systems are able to access the real-time estimation of cognitive and emotional states of the learner, system can automatically adjust the presentation style more interactive and effective if the learner is uninterested. In e-health measurement used to monitor patient feelings about treatment.

Our proposed work implemented using MATLAB version 8.2.0.29 (R2013b) and Intel(R) Core(TM) i3-2330M CPU @ 2.40 GHz processor machine, Windows 7 Professional (64 bit), 6 GB RAM and a 14 MP camera. The result performance shows the efficacy of our suggested method used to recognize the six universal states of emotions. Recognition rate obtained for the proposed system with CK+ database is 94.14 percent. Systems have troublesome to classify inter-class similarity expression (happily surprised and angrily surprised). Our future work is to enhance the performance of the recognition rate by solving the above mentioned issues in the framework.

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